Detection of rubber (*Heavea brasialiensis*) leaf diseases using image processing techniques

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ABSTRACT A big threat occurs in rubber plantations in Indonesia. Leaf disease attacks tens of thousands of hectares of rubber land and threatens agricultural sustainability. This situation makes Indonesian farmers vulnerable to the effects of tree disease, which can be fatal if not treated properly. Detection of plant diseases conventionally is very complex and takes a long time. Natural conditions in Kalimantan make it more difficult for farmers to get treatment for the disease. The early detection of leaf diseases using machine learning techniques is foreseen to be necessary. This study uses leaf disease images to detect the type of leaf diseases, whereby image processing techniques are carried out to determine the characteristics of the disease. In the preprocessing stage, the red, green, blue (RGB) color space was changed to hue, saturation, value (HSV). Then, the K-means segmentation is applied with a value of K=3. The gray level co-occurrence matrix (GLCM) performed the extraction to get the carried out using the Adaptive Neuro-Fuzzy Inference System (ANFIS) with 99% accuracy result for training data and 93% for testing data with a Root Mean Square Error (RMSE) value of 0.113263. The results show that machine learning method has the potential to help in minimizing losses, improve plant quality and quantity, and help for early detection so that the best treatment steps can be taken.

KEYWORDS: Agricultural Technology; Classification; Early Detection; Image Processing; Leaf Disease.
Received 24 May 2023 **Revised** 26 June 2023 **Accepted** 28 June 2023 **Online** 10 July 2023

Original Article

INTRODUCTION

Rubber (*Havea brasiliensis*) has a major contribution in the natural resource export sector to several countries, such as Malaysia, Indonesia, India, etc. Indonesia is a country whose agricultural sector is one of the country's foreign exchange earners. Rubber plantations are able to create jobs and as the main source of household income. However, the obstacles experienced, especially concerning plant diseases, is an important concern. The use of increasingly developed technology can be utilized as a step to detect plant diseases.

The difficulty of communicating with small farmers with existing models (Ali *et al.*, 2020) to implement a decision support system that is used to identify limitations in the production of rubber plants can be observed. Traditionally leaf diseases are only identified visually, and scientific knowledge requires expert approval and a lengthy process. Hence, no rubber leaf disease database can be used by farmers. In addition, disease detection carried out in the laboratory requires expensive equipment and skilled technicians. The research was conducted by (Roy *et al.*, 2019) to determine the response of a large number of genes that are expressed differently for identifying *Corynespora* leaf disease in rubber using Gene Ontology analysis. This disease causes a decrease in the yield of the affected plants. Furthermore, Liu *et al.* (2018) investigated the phylogenetic diversity of Colletotrichum isolates on rubber disease.

The image processing technique is used to simplify the process (Maheswaran *et al.*, 2021). The development of computer vision has been widely used in agriculture to automate the work of experts. In addition, the technology used is very helpful for farmers with little land to achieve the benefits of low maintenance and development costs with high efficiency (Tian *et al.*, 2020). Over the last few years, disease detection research has greatly interested in using image processing, machine learning, deep learning, the Internet of Things, and hyperspectral image analysis (Orchi *et al.*, 2022).

Several researchers carry out the detection of rubber disease by comparing images, as was done by (Yusoff *et al.*, 2019) using edge detection, a primary red, green, and blue (RGB) color model by identifying regions of interest (ROI). This technique is also used in (Abdullah *et al.*, 2007) by applying the optimized artificial neural network (ANN) model produces an accuracy of 70%. Image segmentation can be done in various ways. One of them is the K-segmentation technique (Ramesh and Vydeki, 2020).

This technique was used to divide the diseased, normal and back parts of the image on the leaf using the clustering method. In addition, the Adaptive Neuro-Fuzzy Inference System (ANFIS) is employed (Iraji, 2019) using the tomato image feature to determine its quality by combining various supporting features. The accuracy obtained is 95.5%.

Plant diseases can cause growth inhibition and damage to plant parts, resulting in an immediate reduction in yield or plant death. the problems that arise from farmers are lack of knowledge about the symptoms of diseases that often occur, limited funds, areas that are too far away to be given socialization and visits and the presence of limited experts. In order to support the management of rubber disease, a system is needed that can efficiently identify early symptoms and save time to avoid production losses. Diseases of rubber plants with large losses are generally caused by fungi, while diseases caused by bacteria and viruses do not suffer large losses.

Symptoms seen in plants give signs of disease, usually seen in leaves, fruit, and stems, which differ for each disease. Therefore, disease symptoms seen on the leaves can be used as input image data for disease detection. Artificial intelligence is applied to create a system that can solve problems like an expert. The research uses several image processing techniques to detect and classify rubber plant diseases from the leaf images.

METHODOLOGY

Diseased leaf samples collected from rubber plantations in Tanjung, Tabalong, South Kalimantan, Indonesia by observing the sample plants intensively, identifying symptoms and finding/detecting existing diseases by using expert expertise and knowledge. The software used is the Windows 10 operating system and data processing software using MATLAB R2017b. The hardware is AMD A12-9720P RADEON R7, 12 COMPUTE CORE 4C + 8G 2.70 GHz, 8 GB RAM. The steps were carried out in this work is as follows.

1) Step 1 was the leaves collected and taken as a dataset for identification.
2) Step 2 was the image dataset is pre-processed to remove noise at this stage.
3) Step 3 was the image which applied the K-means segmentation algorithm as done by Ramesh and Vydeki (2020).
4) Step 4 was the implementation of gray level co-occurrence matrix (GLCM) feature extraction on the image which is carried out to get the features classified. Correspondingly, the GLCM feature is used as a database in the next process. The GLCM texture considers the relationship between two pixels at the same time and is called the reference and adjacent pixels (Al-windi *et al.*, 2021).
5) Step 5 was the classification algorithm which is applied to the features obtained using ANFIS. This is done to get the membership value using a membership function type approach such as bell (gbellmf), gaussian (gaussmf), trapezium (trapmf) and triangle (trimf), which were tested for accuracy.

The studied diseases were *Colletotrichum* causing Leaf Fall Disease, *Corynespora* causing Leaf Fall Disease, and *Oidium* causing Powdery Mildew as shown in Figure 1. Leaves that show symptoms were photographed using a white background in their collection. The total sampling to be used is 150 photos with each disease amounting to 50 images. Training data is taken as much as 70% of the data, namely 35 images, while for testing data was expressed as much as 30% of 15 images. Leaf symptom data were collected according to the knowledge of experts. After taking the photo, the sample was verified and identified by experts according to the type of disease.

a b c

Figure 1. Original image leaf rubber diseases: *a) Colletotrichum* causing Leaf Fall Disease *b) Corynespora* causing Leaf Fall Disease *c) Oidium* causing Powdery Mildew.

RESULT AND DISCUSSION

Image Preprocessing

The obtained images pre-processed to increase the grayscale contrast. In addition, image processing is usually used for image resizing, filters, and noise reduction (Pavithra & Palanisamy, 2017). The step taken in this stage is the image extracted into the RGB image's green component. Subsequently, it is converted to hue, saturation, and value (HSV) color space. This is done to set a different color for the foreground and background of the image compared to the equivalent RGB image.

Conversion is then applied by calculating the components of HSV. These three components make up the HSV color space where 'Hue' represents the color, 'Saturation' represents the amount of color mixed with white, and 'Value' represents the amount of each color mixed with black. The threshold value of the Hue component is used to remove unwanted background and noise from the image. Other than that, noise removal is performed to improve the quality of the leaf image for further processing.

Image Segmentation

In the image segmentation stage, the image of leaves infected with the pathogens are segmented according to their characteristics. Noted that the K-means clustering approach is used for image segmentation into homogeneous regions. The value of K-means refers to the number of clusters selected for the initialization. In this study, K=3 is used as the number of clusters. In this process, the image is partitioned into several parts according to identical or similar features as shown in Table 1.

Image Feature Extraction

In the next step, the image segmentation was performed and features were extracted to get the desired attributes which is analyzed later. GLCM is a feature extraction method that describes the spatial relationship between pairs of pixels with a certain gray-level intensity in an image (Al-windi *et al.*, 2021).

GLCM generates statistical features used in disease detection. Its features describe the texture associated with certain disease symptoms quantitatively relatively quickly. The use of GLCM helps to identify textures or distinctive differences that appear in infected leaf data. Smooth texture differences at very small pixel levels can be captured with GLCM. By analyzing the texture of the image, GLCM can reveal important morphological characteristics for the diagnosis of leaf. Calculation of computation time on GLCM may vary. To overcome this, the approach taken is to perform image preprocessing and segmentation, selecting efficient texture features, and using high computational resources.

The type of disease in leaves are detected, six features of GLCM were used in this study, namely contrast, correlation, energy, homogeneity, entropy, and inverse difference. The features obtained after extraction were analyzed to determine the diseases is shown in Table 2.

Table 1. Image segmentation step for each disease image.

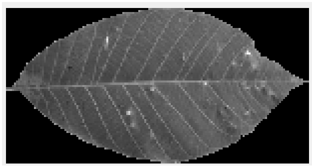
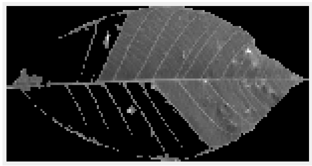
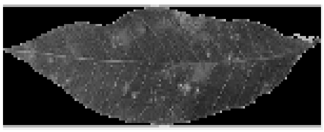
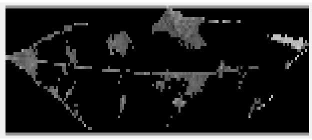
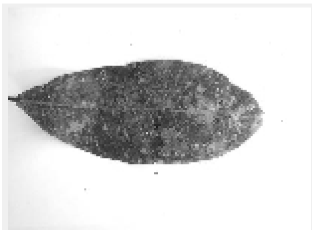
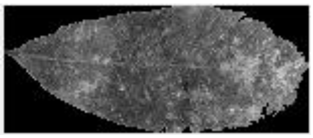
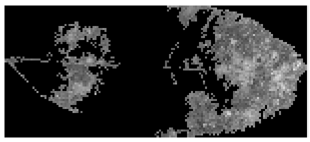
Leaf diseases	K=1	K=2	K=3
Colletotrihum			
Corynespora			
Oidium			

Table 2. Value of Feature GLCM Extraction leaf rubber disease.

Value of Feature GLCM	Image of Leaf Disease		
	Colletotrichum	*Corynespora*	*Oidium*
Contrast	0.40033	0.50238	0.74693
Correlation	0.89567	0.74895	0.85678
Energy	0.39558	0.72578	0.43773
Homogeneity	0.93488	0.94406	0.89243
Entropy	1.3984	0.81266	1.5264
Inverse Difference	0.99452	0.99334	0.98978

Classification

The input feature used is the GLCM feature that has been obtained for better pattern recognition. GLCM provides information about image morphology, while ANFIS can study the relationship between features and the presence of leaf disease. Thus, the ANFIS algorithm can make decisions based on the texture features extracted through GLCM. The ANFIS combines the explicit knowledge representation of Fuzzy Inference System with the learning power of Artificial Neural Networks, therefore it is a very powerful approach to build complex relationship between a set of input and output data.

Table 3. ANFIS Model training results with membership function.

Epochs	Membership Function	Accuracy	Time (second)	Data True	Data False
10	Gbellmf	98.09 %	7.0567	103	2
	Gaussmf	96.19 %	5.272	101	4
	Trimf	85.72 %	5.325	90	15
	Trapmf	**99.05 %**	0.99297	104	1
50	Gbellmf	**99.05 %**	28.9861	104	1
	Gaussmf	96.19 %	32.5176	101	4
	Trimf	85.71 %	27.7583	90	15
	Trapmf	**99.05 %**	0.94757	104	1
100	Gbellmf	**99.05%**	57.9732	104	1
	Gaussmf	96.19 %	58.3087	101	4
	Trimf	85.71 %	68.2071	90	15
	Trapmf	**99.05 %**	1.1363	104	1

Table 4. ANFIS Model testing result with membership function.

Epochs	Membership Function	Accuracy	Time (second)	Data True	Data False
10	Gbellmf	62.22 %	0.0037253	28	17
	Gaussmf	62.22 %	0.0042183	28	17
	Trimf	53.33 %	0.0038013	24	21
	Trapmf	46.67	0.00318	21	24
50	Gbellmf	86.67 %	0.003758	39	6
	Gaussmf	62.22 %	0.0039269	28	17
	Trimf	53.33 %	0.0035841	24	21
	Trapmf	46.67	0.00314	21	24
100	Gbellmf	**93.33 %**	0.00411	42	3
	Gaussmf	62.22 %	0.0034147	28	17
	Trimf	53.33 %	0.0047895	24	21
	Trapmf	46.67 %	0.0036615	21	24

The model with Gbellmf membership functions gave the best performance among all given models of the ANFIS is obtained in Table 3 and Table 4 for the membership function using, which holds the highest accuracy value of 99% for training and 93% for testing. Leaf images have variations in texture, color and shape. Gbellmf function has a sharp peak, this function can well recognize the position of the peaks in the visual distribution associated with the disease well. So ANFIS can better identify the GLCM texture features in leaf images. The capability ANFIS system in producing such reasonable result indicated that this approach has potentially to be used as leaf disease detection of rubber tree in the Tabalong. Hence, it can be concluded that the ANFIS method can detect disease properly and reliably in recognizing image characteristics.

CONCLUSION

The results of this study indicate that the proposed plant disease detection was reliable in correctly detecting 42 leafs with disease from the 45 images tested. By using this technique, a small sample can still represent the population in a balanced and accurate manner. The ANFIS algorithm classification method using the trapezoidal membership function type (Gbellmf) and epoch 100 gives the lowest Root Mean Square Error (RMSE) value of 0.113263 with the highest accuracy value of 99% in training and 93% in testing. By selecting the GLCM features and integrating with the ANFIS algorithm, we obtain a reliable and accurate approach in detecting leaf diseases. The number of samples can be added for further research. The success of this system depends on the quality of the data used, proper feature extraction, proper feature selection, good model design, and appropriate settings of the ANFIS algorithm. This can minimize losses, improve the quality and quantity of plants, as well as assist early detection so that the best handling steps can be taken.

ACKNOWLEDGEMENTS

The author would like to thank Universitas Islam Kalimantan Muhammad Arsyad Al-Banjari and Dinas Perkebunan Tanjung, Tabalong as well as Faculty of Computing and Meta-Technology, Universiti Pendidikan Sultan Idris, Malaysia for all the supports.

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